Heterogeneity of long-run technical efficiency of German dairy farms

Skevas, Ioannis; Emvalomatis, Grigorios; Brümmer, Bernhard

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Heterogeneity of long-run technical efficiency of German dairy farms: a Bayesian approach

Ioannis Skevas, Grigorios Emvalomatisb and Bernhard Brümmerc (fn1)

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Abstract

In parametric efficiency studies, two alternative approaches exist to *~~that can~~ provide an estimate of the long-run efficiency of firms: the dynamic stochastic frontier model and the generalized true random-effects model. We extend the former in order to allow for heterogeneity in the long-run technical efficiency of firms. This model is* based *~~justified by drawing~~ on potential differences in firm-specific characteristics and in firms' inefficiency persistence. The model is applied to an unbalanced micro-panel of German dairy farms* over *~~that covers~~ the period ~~from~~ 1999 to 2009. Estimation of long-run technical efficiency and inefficiency persistence is based on an output distance function representation of the production technology and* estimated *~~performed~~ in a Bayesian framework. The results suggest that heterogeneity in long-run technical efficiency of farms is mostly attributed to discrepancies in farm-specific factors rather than differences in farms' inefficiency persistence. Farm size is positively related to long-run technical efficiency while subsidies exert a negative effect on the long-run technical efficiency of farms. Inefficiency persistence is found to be very high, but heterogeneity in this persistence is low.*

Keywords: *Dynamic stochastic frontier; long-run technical efficiency; inefficiency persistence; heterogeneity; dairy farms.*

JEL Classifications: C11, C23, D21 D24

fn1: Ioannis Skevas is the contact author - iskevas@gwdg.de. Both he and Bernhard Brümmer are with the Department of Agricultural Economics and Rural Development, University of Göttingen, Germany. Grigorios Emvalomatis is in the Department of Economic Studies, University of Dundee, United Kingdom. The paper has been greatly benefited from the comments of Andrew (Andy) Johnson who acted as a designated discussant for a preliminary version of the paper during the 14th European Workshop on Efficiency and Productivity Analysis in Helsinki, Finland. The paper has also profited from informal talks with several participants of the workshop, and from comments by anonymous reveiwers. Any errors or omissions are the sole responsibility of the authors.

1 Introduction

Agricultural investment is often referred to as the main engine of farm productivity improvement and considered to be necessary for farms to catch up with frontier shifts in order to ~~avoid being driven out of business~~ survive. ~~In a capital-intensive agricultural environment, s~~Such investment is associated with the replacement of existing capital, ~~the~~ an increase in the capital stock or the adoption of technological innovations (Kapelko et al., 2015). Hence, continuous agricultural investment can ~~assure~~ lead to frequent changes in farms' production process, facilitating the use of existing knowledge or the generation of new technology. However, the adjustment cost hypothesis described by Penrose (1959) and Eisner et al. (1963), and taken further by Ferguson (1966), states that the existence of adjustment costs prevents the decision-making units from instantaneously adjusting their quasi-fixed inputs to their long-run equilibrium values. Examples of adjustment costs are expansion-related expenses, constraints on credit sources and learning and training costs that are related to the time spent by the operator to acquire knowledge and experience using the new resources (Stefanou, 2009). This costly adjustment provides farm operators with an incentive to remain partly inefficient in the short-run, resulting in persistence of their inefficiency over time. ~~Besides, inefficiency persistence may differ among farms because of discrepancies in the speed that technological innovations are adopted. For instance~~ Also, disparities in the managerial skills and motivation of the farm operators may affect the speed of the introduction of a new technology (Gardebroek and Oude Lansink, 2004). In addition, discrepancies in the cognitive capacity and experience of farm operators may result in less/more time devoted to becoming familiar with the new technology. Hence, differences in adjustment costs across farms may result in varying degrees of inefficiency persistence among them.

The adjustment cost hypothesis can also provide the basis for the distinction between short and long-run inefficiency. The difference between these two concepts is illustrated by an example. Suppose that a system is currently in equilibrium when a new technology ~~arises.~~ arrives. If there were no adjustment costs ~~present,~~ farm operators would instantaneously adopt the new technology and would reach their desir~~able~~ed efficiency levels in the short-run. However, if adjustment costs exist, the optimal strategy for farm operators would be to remain inefficient in the short-run and reach their targeted efficiency levels in the long-run. Dependent on the level of adjustment costs and on farm-specific characteristics, farms may consider different reactions to the ~~shock introduced by~~ introduction of the new technology. Despite reacting differently, decision makers will take into account their long-run objective (which may differ among farms) in their current production plans. ~~Hence, long-run inefficiency is perceived as a flow that measures the failure to optimize in the current period where farms always operate. The term “long-run” stems from the fact that farms’ decisions are made in the short-run but with a view in the future. On the other hand, s~~Short-run inefficiency completely ignores the presence of adjustment costs and that current production decisions may affect future outcomes. ~~It simply takes a snapshot of the current position of the production frontier, and quantifies the deviation of farms from this frontier.~~ Few parametric efficiency studies recogni~~zed~~se the intertemporal nature of farms’ decision-process and distinguis~~ed~~h between short-run and long-run efficiency. However, as the effect of farm-specific factors on short-run efficiency is well documented, surprisingly, their impact on long-run efficiency has been ~~completely~~ largely disregarded. Particularly in agriculture, heterogeneity in farm size and the ~~high~~ extent of regulation may be responsible for differences in the long-run efficiency of farms.

~~In this paper w~~We propose a dynamic stochastic frontier model that can provide an estimate of farm-specific long-run efficiency that varies due to farm-specific characteristics and varying degrees of their inefficiency persistence. Furthermore,

we also propose
an alternative specification for modeling heterogeneity in inefficiency persistence over time ~~is proposed~~. The next section ~~offers~~ provides a review of the literature. In Section 3, the modeling approach is described and Bayesian techniques are detailed. The model is applied to a micro-panel of German dairy farms and Section 4 describes the data used and the empirical specification of the model. Section 5 presents the results, ~~while concluding remarks are provided in S~~ and section 6. concludes

2 Literature review

Two alternative approaches exist that take into account adjustment costs and distinguish between short-run and long-run inefficiency using the parametric technique of Stochastic Frontier Analysis (SFA) (Aigner et al., 1977; Meeusen and van den Broeck, 1977)[1]. The first approach~~,~~ is based on the generalized true random effects model introduced by Tsionas and Kumbhakar (2014) in a Bayesian framework, and involves the specification of an one-sided time-invariant error term and an one-sided time-varying error term in the production frontier. The first error term aims to capture the so-called persistent or long-run inefficiency while~~,~~ the latter~~,~~ aims to capture the so-called transient or short-run inefficiency. Identification of these two inefficiency components, in the presence of time-invariant firm characteristics (i.e. unobserved heterogeneity) and time-varying statistical noise, is achieved through the use of one-sided distributions for the two inefficiency components. Since its introduction, this novel approach has been used by several ~~other~~ empirical studies. For instance, Filippini and Greene (2016) and Filippini and Hunt (2015), present the frequentist way to estimate the generalized true random effects model using the method of simulated maximum likelihood, while

[1] For a review of non-parametric dynamic efficiency studies that have used Data Envelopment Analysis (DEA), see Fallah-Fini et al. (2014).

Badunenko and Kumbhakar (2016) examine the robustness of the model due to concerns related mainly to the identification of the four error components.

The second approach~~,~~ accounts in a more comprehensive way for the consequences of costly adjustment of quasi-fixed inputs, and the resulting persistence of inefficiency. More precisely, Ahn and Sickles (2000) specified an autoregressive process on firm-specific efficiency scores to account for persistence of shocks in firm-level efficiency. In the presence of ~~the aforementioned~~ adjustment costs, this model recognizes that inefficiency is not likely to disappear over time. Criticism related to the specification of an autoregressive process on a nonnegative variable~~,~~ has led Tsionas (2006) to specify an autoregressive process on transformed efficiency that can take any value on the real line. The same approach was followed by Emvalomatis et al. (2011), Emvalomatis (2012), Galán et al. (2015), and Lambarraa et al. (2016). This model, as in the case of the generalized true random effects model, can provide an estimate of both the short- and long-run firm-level efficiency. The short-run efficiency is derived based on the distance of the firms from the production possibilities frontier, while~~,~~ long-run efficiency corresponds to the steady-state value of efficiency from the specification of the autoregressive process.

However, there are some important differences between the two approaches in the use of the efficiency terms. Short-run efficiency in the dynamic efficiency model has a dynamic link, as efficiency in the current period depends on the efficiency from the previous period. In the generalized true random effects model, transient efficiency is a one-sided time-varying error component that does not assume any relationship between efficiency in different time periods. Furthermore, in the dynamic efficiency model, long-run efficiency is realized if the system reaches the equilibrium. On the contrary, the generalized true random effects model assumes that the system is always in the equilibrium and persistent efficiency is captured by a one-sided time-invariant error term.

~~The studies of~~ Tsionas (2006) and Lambarraa et al. (2016) fail to derive the long-run efficiency of firms due to the specification of time-varying covariates in the autoregressive process. Emvalomatis et al. (2011) and Emvalomatis (2012) provide estimates for the long-run efficiency scores assuming that all firms reach a common long-run efficiency level. In contrast, ~~Unlike the aforementioned studies, the study of~~ Galán et al. (2015) recogni~~zes~~se that differences in firms' adjustment costs may result in different degree of their inefficiency persistence, but, as in Tsionas (2006), the specification of time-varying variables in the autoregressive process does not allow them to derive long-run measures of efficiency. The only exception that combines the specification of heterogeneity in inefficiency persistence and the derivation of firm-specific long-run efficiency scores, is the work of Ahn and Sickles (2000). However, heterogeneity in firm-specific long-run efficiency occurs only due to differences in firms' (unobserved) management and different speed of adoption of a new technology, without taking into account any observable firm-specific factors.

From this short review we observe that neither of the two streams of parametric efficiency studies, that can provide estimates of short-run and long-run efficiency, have yet ~~not~~ provided any empirical evidence on the impact of firm-specific characteristics on the long-run efficiency of firms. In what follows, we present an extension to the dynamic stochastic frontier model that allows for the impact of firm-specific characteristics on the long-run technical efficiency of firms.

3 Modelling Approach and Estimation

We consider the typical stochastic frontier model and employ an output distance function to account for the multi-output nature of the production technology.

Assuming that a vector of outputs $\mathbf{y} \in R_{+}^{M}$ M is produced by a vector of inputs $\mathbf{x} \in R_{+}^{N}$, the output distance function is defined as:

$$D_o(\mathbf{x}, \mathbf{y}, t) = \min \left\{ \theta : \frac{\mathbf{y}}{\theta} \text{ can be produced by } \mathbf{x} \text{ in period t} \right\} \tag{1}$$

The output distance function gives the minimum amount by which the output vector can be deflated given the input vector. It assumes values in the unit interval and the locus of points for which $D_o(\mathbf{x}, \mathbf{y}, t) = 1$ defines the boundary of the production possibilities set. The technical efficiency of firm i in period t is defined as $TE_{it} = D_o(\mathbf{x}_{it}, \mathbf{y}_{it}, t)$. Taking the logarithm of both sides of this expression, imposing the condition of linear homogeneity in outputs of the output distance function, and appending an error term leads to the econometric version of the distance function:

$$-\log y_{it}^{m} = \log D_o\left(\mathbf{x}_{it}, \frac{\mathbf{y}_{it}}{y_{it}^{m}}, t\right) + v_{it} - \log(TE_{it}) \tag{2}$$

where y_{it}^{m} is the normalizing output and v_{it} is an error term that captures statistical noise. Letting $\mathbf{y}_{it}$ be the dependent variable in equation (2) and the logarithm of the distance function a linear function of parameters and functional transformations of its arguments, the estimable form of the distance function can be written as:

$$\mathbf{y}_{it} = \mathbf{x}_{it}^{'}\boldsymbol{\beta} + v_{it} - \log(TE_{it}) \qquad v_{it} \sim \mathcal{N}(0, \sigma_v^2) \tag{3}$$

where $\mathbf{y}_{it}$ is minus the logarithm of the normalizing output, $\mathbf{x}_{it}^{'}$ is a vector of covariates, $\boldsymbol{\beta}$ is a vector of parameters to be estimated and TE_{it} is the technical efficiency of firm i in period t. For estimation purposes, equation (3) can be seen as a typical cost stochastic frontier.

However, the relevant literature has raised concerns related to potential endogeneity of inputs and output ratios. Kumbhakar (2013) argues that if inputs and output ratios are not exogenous, the use of a distance function is problematic as it suffers from endogeneity. Nevertheless, we assume that producers (given the input price ratios) decide how much of each input to use, and given that, they maximize output revenue/profit. Furthermore, given the main argument of the paper concerning quasi-fixity of most of the inputs, we assume that inputs are exogenously given. In terms of output ratios, Sipiläinen et al. (2014) state that output ratios may not be endogenous dependent on how the two outputs are affected by the noise component. Therefore, the issue of endogeneity depends on the specific application. In the case of specialized dairy farms that this article is concerned with, outputs are not diverse, and therefore the endogeneity problem may be negligible.

Following Tsionas (2006), Emvalomatis et al. (2011), Emvalomatis (2012), Galán et al. (2015), and Lambarraa et al. (2016), we consider a dynamic stochastic frontier model that specifies an autoregressive process on firm-specific technical efficiency[2]. However, in this study, as in Galán et al. (2015) we allow for firm-specific inefficiency persistence and recognize that heterogeneity in terms of the adjustment costs and the managerial characteristics of farms may affect the degree of persistence. We define a latent-state variable, $s_{it} = \log(\frac{TE_{it}}{1-TE_{it}})$, as the logistic transformation of technical efficiency so that we project TE_{it} from the unit interval to the real line and we assume the following autoregressive process on s_{it}:

$$s_{it} = \mathbf{z}_i^{'}\boldsymbol{\delta} + \rho_i s_{i,t-1} + \xi_{it} \qquad \xi_{it} \sim \mathcal{N}(0, \sigma_\xi^2) \tag{4}$$

[2]Note that this is a reduced form of a dynamic model as adjustment costs are not modelled explicitely but are rather implied. However, the term "dynamic" is used as this is the standard wording in the literature.

$$s_{i0} = \frac{\mathbf{z}_i'\boldsymbol{\delta}}{1-\rho_i} + \xi_{i0} \qquad \xi_{i0} \sim \mathcal{N}(0, \sigma^2_{\xi 0}) \tag{5}$$

In this case ρ_i is an elasticity that measures the firm-specific percentage change in the efficiency to inefficiency ratio that is transferred from one period to the next. Stationarity of the s series ensures that the expected value of s does not diverge to either positive or negative infinity and therefore, technical efficiency will not approach unity or zero. Using functional transformations, the firm-specific inefficiency persistence parameter is restricted on the unit interval. A value of ρ_i close to one indicates high inefficiency persistence and that high adjustment costs result in sluggish adjustment of quasi-fixed factors. Besides, given the one-to-one transformation from s to TE, the steady-state value of s is directly interpreted as a long-run expected value for technical efficiency (LRTE). In this case, the expected value of LRTE corresponds to the expectation of $[1 + \exp\{\mathbf{z}_i'\boldsymbol{\delta}/1 - \rho_i\}]^{-1}$ and is interpreted as the expected value of efficiency that will prevail in the sector in the long-run marginally with respect to $s_{i,t-1}$. Besides, this value will be firm-specific due to differences in firm-specific characteristics and potential heterogeneity in firms' inefficiency persistence.

Moving to the modeling of firm-specific inefficiency persistence, Galán et al. (2015) used a hierarchical structure allowing the inefficiency persistence parameter ρ_i to take values between -1 and 1. More specifically, they assumed that $\rho_i = 2k_i - 1$ and sampled k_i from a Beta distribution. However, we argue that it is rather unlikely to observe negative autocorrelations of efficiency in the adjustment towards the long-run equilibrium, while sampling from a Beta distribution can be computationally troublesome. With the intention to restrict the inefficiency persistence parameter, ρ_i, on the unit interval, we specify $\rho_i = \frac{\exp(h_i)}{1+\exp(h_i}$ and we assume the following relationship:

$$h_i = \mu + \omega_i \qquad \omega_i \sim \mathcal{N}(0, \sigma_\omega^2) \tag{6}$$

In this framework, h_i is a draw from a Normal distribution with common mean μ, and variance σ_ω^2. Hence, our modeling approach not only restricts inefficiency persistence on the unit interval but also specifies a less computationally demanding sampling distribution for ρ_i. According to this transformation, h_i follows a logit-Normal distribution with negative values of μ resulting in very low inefficiency persistence, positive and low values (e.g. from 2 to 4) in high inefficiency persistence, while, positive and high values imply that inefficiency persistence approaches unity. Finally, given that the variables in $\mathbf{z}$ capture part of firm's unobserved heterogeneity, we do not include random effects in the production frontier. We use Bayesian techniques to estimate the model described in equations (4-7). We define s_i to be a $T_i \times 1$ vector of the latent-state variable of the transformed technical efficiency for firm i and h to be an $N \times 1$ vector of the latent-state variables of the transformed inefficiency persistence. Finally, we collect all structural parameters to be estimated to a vector $\theta = [\boldsymbol{\beta}, \sigma_v, \boldsymbol{\delta}, \sigma_\xi, \mu, \sigma_\omega]'$. The complete data likelihood of the structural parameters and latent states is:

$$\begin{aligned}
p(\mathbf{y}, \{\mathbf{s}_i\}, \mathbf{h}|\boldsymbol{\theta}, \mathbf{X}, \mathbf{Z}) &= p(\mathbf{y}|\{\boldsymbol{s_i}\}, \boldsymbol{\beta}, \sigma_v, \mathbf{X}) \times p(\{\boldsymbol{s_i}\}|\mathbf{h}, \boldsymbol{\delta}, \sigma_\xi, \mathbf{Z}) \times p(\mathbf{h}|\mu, \sigma_\omega) \\
&= \frac{1}{(2\pi\sigma_v^2)^{\sum_{i=1}^N \frac{T_i}{2}}} \exp\left\{ -\sum_{i=1}^{N}\sum_{t=0}^{T_i-1} \frac{(\mathbf{y}_{it} - \mathbf{x}_{it}'\boldsymbol{\beta} + \log TE_{it})^2}{2\sigma_v^2} \right\} \\
&\times \frac{1}{(2\pi\sigma_{\xi 0}^2)^{\frac{N}{2}}} \exp\left\{ -\sum_{i=1}^{N} \frac{(s_{i0} - \mathbf{z}_i'\boldsymbol{\delta})^2}{2\sigma_{\xi 0}^2} \right\} \\
&\times \frac{1}{(2\pi\sigma_\xi^2)^{\sum_{i=1}^N \frac{(T_i-1)}{2}}} \exp\left\{ -\sum_{i=1}^{N}\sum_{t=1}^{T_i-1} \frac{(s_{it} - \mathbf{z}_i'\boldsymbol{\delta} - \rho_i s_{i,t-1})^2}{2\sigma_\xi^2} \right\} \\
&\times \frac{1}{(2\pi\sigma_\omega^2)^{\frac{N}{2}}} \exp\left\{ -\sum_{i=1}^{N} \frac{(h_i - \mu)^2}{2\sigma_\omega^2} \right\}
\end{aligned} \tag{7}$$

where $\mathbf{y}$ is the stacked vector of the values of the dependent variable over i and t, $\mathbf{X}$ is the matrix of covariates in equation (3) and $\mathbf{Z}$ is the matrix of covariates in equations (4) and (5). The first line of equation (7) is due to the normality assumption of v_{it}. The second line is due to the normality assumption of the error term in equation (5), representing the steady-state value of s, whose expectation can be transformed to the long-run technical efficiency of firms. The third line is due to the normality assumption of the error component in equation (4). Finally, the last term of equation (7) comes from the normality assumption of ω_i in equation (6).

Using Bayes' rule the joint posterior density of the model's parameters and latent states is:

$$\pi(\boldsymbol{\theta}, \{\boldsymbol{s_i}\}, \mathbf{h}|\mathbf{y}, \mathbf{X}, \mathbf{Z}) \propto p(\mathbf{y}, \{\mathbf{s}_i\}, \mathbf{h}|\boldsymbol{\theta}, \mathbf{X}, \mathbf{Z}) \times p(\boldsymbol{\theta}) \tag{8}$$

where $p(\mathbf{y}, \{\mathbf{s}_i\}, \mathbf{h}|\boldsymbol{\theta}, \mathbf{X}, \mathbf{Z})$ is given by equation (7) and $p(\boldsymbol{\theta})$ corresponds to the product of all the prior densities. The priors that we impose to the parameters are the following:

- A multivariate normal density is used for the prior density of the vectors $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$. Prior means are set equal to zero while the prior covariance matrices are diagonal with a value of 1000 on the diagonal entries. The fact that the variance is set to such a large value implies that the prior will have minimal effect on the results. This prior is conjugate.

- A Gamma prior is used for $\frac{1}{\sigma_v^2}$, $\frac{1}{\sigma_\xi^2}$, and $\frac{1}{\sigma_\omega^2}$ since this prior is conjugate. For $\frac{1}{\sigma_v^2}$ the shape and scale hyper-parameters are both set equal to 0.001, for $\frac{1}{\sigma_\xi^2}$ both the shape and scale hyper-parameters are set equal to 0.01, and for $\frac{1}{\sigma_\omega^2}$ the shape hyper-parameter is set equal to 0.1 and the scale hyper-parameter is set equal to 0.01. Note that the priors imposed on $\frac{1}{\sigma_\xi^2}$, and $\frac{1}{\sigma_\omega^2}$ are a bit more informative than that imposed on $\frac{1}{\sigma_v^2}$, because they correspond to hidden-state equations.

- We impose a normal prior for the parameter μ. The prior mean is set equal to 2.3, while the prior variance is set equal to 10. Based on the transformation used in equation (6), this prior mean value results in a high value for inefficiency persistence ρ_i, as previous studies have also reported.

We use Markov chain Monte Carlo (MCMC) simulations (see Koop et al. (1995) for an application to stochastic frontier models) to sample from the posterior. To draw samples from the posterior for the latent states, $\{\mathbf{s}_i\}$ and $\mathbf{h}$, data augmentation techniques are also used (Tanner and Wong, 1987). The priors specified for $\boldsymbol{\beta}$, $\boldsymbol{\delta}$ and μ, and the variances are conjugate and, therefore, Gibbs updates are used. The complete conditionals for $\{\mathbf{s}_i\}$ and $\mathbf{h}$ do not belong to any known distributional family and, therefore, Metropolis-Hastings updates are used. The MCMC techniques used involve 10 chains and 130,000 iterations with a burn-in phase of 50,000 iterations being used to remove the influence of the initial values. Since the Metropolis-Hastings algorithm has the potential of generating highly correlated draws, every one in 10 draws were retained to reduce autocorrelation in the samples. Hence, every chain contributes 8,000 draws, resulting in a total of 80,000 retained draws from the posterior.

4 Data and empirical specification

The data used for this application are provided by the Farm Accountancy Data Network (FADN)[3]. The accounting data that FADN provides are collected regionally using a common questionnaire across all EU Member States. The dataset contains farm-level information on physical and structural data of farms, such as farms' location, milk output, livestock units, as well as economic and financial data, such as production costs, subsidies and quotas. FADN uses a stratified random sampling scheme in which farms remain in the panel for a period of four to five years on average, although there are cases where farms remain for more than ten years.

The part of the dataset used here contains such information for German dairy farms and covers the period from 1999 to 2009. This study focuses on farms engaged primarily in dairy production, and for this purpose we have selected farms whose revenue from sales of cow's milk, beef and veal comprise at least 66% of their total revenues for every year the farm is observed. Additionally, considering the dynamic nature of our model, we have selected farms that are observed for at least four consecutive years. The final dataset consists of an unbalanced panel of 1,691 farms with a total of 13,384 observations.

The output distance function in equation (2) is specified in two outputs:

1. Deflated revenues from sales of cow's milk and milk products (milk)

2. Deflated revenues plus change in valuation of beef and veal, pigmeat, sheep and goats, and poultry meat, plus deflated revenues from sales of other livestock and products (other)

The reported revenues are deflated with price indices obtained from EUROSTAT, using 2000 as the base year.

[3]Data source: EU-FADN - DG AGRI.

Six inputs are specified in equation (2):

1. Buildings and machinery (K) are measured in deflated book value [4] . A Törnqvist index was constructed using price indices for each of the two components. The total reported value was then deflated using the Törnqvist index.

2. Total labor (L) is measured in man-hours and consists of family, as well as hired labor.

3. Total utilized agricultural area (A) is measured in hectares and includes owned and rented land.

4. Materials and services (M) are measured in deflated value. This input consists of ten categories of inputs: seeds and plants, fertilizers, crop protection, energy, other livestock-specific costs, other crop-specific costs, forestry-specific costs, feed for pigs and poultry, contract work and other direct inputs. A Törnqvist index was constructed using expenditure and price indices for each input. The total reported value was then deflated using the Törnqvist index.

5. Total livestock units (S) is measured in livestock units and includes equines, cattle, sheep, goats, pigs and poultry that are present at the holding.

6. Purchased feed (F) is measured in deflated value. It includes feed, concentrated feedingstuffs, coarse fodder, as well as expenditure for the use of forage land. The value of feed produced within the farm is excluded.

Dummy variables for eastern, western, northern and southern (base category) Germany are used to capture discrepancies in technology and climatic conditions.

[4] Brümmer et al. (2002) have included livestock units in their capital index. We decided to specify livestock units as a separate input to identify its individual effect on production.

Finally, the **z** vector in equations (5)-(6) includes two variables[5] : the economic size of farms expressed in hundreds of European Size Units (ESU) and the total amount of subsidies[6] that farms receive in thousands of euros. Farms with large economic farm size are more business/market oriented and may put more managerial effort in terms of the use of mental labor in the production process compared to those with smaller economic farm size. This may be reflected in differences in their efficiency. For instance, Latruffe et al. (2004), Latruffe et al. (2008), Bojnec and Latruffe (2011) and Zhu et al. (2012), find that ~~bigger~~ larger farm size is associated with higher efficiency levels. The effect of subsidies on efficiency is more disputable. On the one hand, subsidies may affect efficiency negatively as~~,~~ their income effect nature~~,~~ may reduce the motivation of farm operators to work efficiently (Hadley, 2006; Bojnec and Latruffe, 2009; Zhu and Oude Lansink, 2010; Zhu et al., 2011, Zhu et al., 2012; Bojnec and Latruffe, 2013). On the other hand, if subsidies act as an investment tool, they may increase the efficiency of farms (Rizov et al., 2013). In our case, decoupled payments comprise approximately 65% of the total amount of subsidies that farms receive. Hence, we expect that subsidies will negatively affect efficiency, since~~,~~ decoupled payments are independent from production quantities and therefore~~,~~ may be simply seen as an additional income source. The two aforementioned variables are specified as time-invariant for two main reasons. First, the interpretation of LRTE would have no meaning if the variables were changing over time. Second, the size of the

[5] Inclusion of additional variables is possible but time-invariant z variables needed to be considered to be able to derive long-run efficiency scores. Hence, we were unable to include additional relevant variables that vary significantly over time.

[6] This variable consists of subsidies on crops, livestock, other subsidies (related to forestry, environmental programs etc.), subsidies on intermediate consumption and external factors, and decoupled payments. Decoupled payments comprise almost 65% of the total subsidies that farms receive, and since these payments are independent from production volumes we assume that subsidies are exogenously given.

farms and the amount of subsidies that farms receive change slightly across time and therefore a time-invariant specification can be representative of the actual behavior of farms[7]. Summary statistics of the models' variables are shown ~~appear~~ in Table 1.

Table 1

Summary statistics of the models' variables

Variable	**Mean**	**SD**	**5%**	**95%**
Cow's milk (1,000€)	144.47	213.84	32.43	350.98
Other output (1,000€)	26.20	30.44	4.36	70.23
Capital (1,000€)	195.83	249.13	28.96	485.38
Labo(u)r (1,000 man-hours)	3.97	5.99	1.80	7.20
Land (hectares)	77.41	132.29	19.08	173.47
Materials (1,000€)	60.25	98.55	13.08	142.79
Livestock (livestock units)	108.17	130.41	32.06	241.81
Purchased feed (1,000€)	27.63	55.76	2.28	73.38
ESU (100 ESU)	0.89	1.25	0.25	1.98
Subsidies (100,000€)	0.31	0.64	0.04	0.72

We use an output distance function for the following reasons. First, despite the milk quota system restricting milk production, farms still have the opportunity to lease and purchase milk quota. Second, given the main argument of the paper concerning sluggish adjustment of quasi-fixed factors of production, inputs like capital and labor are restricted to immediate changes. The distance function is specified as translog in inputs ($\mathbf{x}$), outputs ($\mathbf{y}$), and time trend. Using the estimable form of equation (2), the distance function is written as:

[7] We compute farm-specific coefficients of variation for ESU and subsidies by dividing every farm's standard deviation in the respective variable by the farm's mean. Figure A1 in the on-line appendix presents histograms of the coefficient of variation for ESU and subsidies.

$$
\begin{aligned}
-\log y_{it}^{m} = {} & \alpha_0 + \sum_k \alpha_k \log x_{it}^{k} + \sum_l \beta_l \log\left(\frac{y_{it}^{l}}{y_{it}^{m}}\right) \\
& + \frac{1}{2}\sum_l \sum_p \alpha_{kp} \log x_{it}^{k} \log x_{it}^{p} \\
& + \frac{1}{2}\sum_l \sum_q \beta_{lq} \log\left(\frac{y_{it}^{l}}{y_{it}^{m}}\right) \log\left(\frac{y_{it}^{l}}{y_{it}^{m}}\right) \\
& + \frac{1}{2}\sum_k \sum_l \zeta_{kl} \log x_{it}^{k} \log\left(\frac{y_{it}^{l}}{y_{it}^{m}}\right) \\
& + \eta_1 t + \eta_2 t^2 + \sum_k \lambda_k t \log x_{it}^{k} \\
& + \sum_l \xi_l t \log\left(\frac{y_{it}^{l}}{y_{it}^{m}}\right) + v_{it} + \log(TE_{it})
\end{aligned}
\tag{9}
$$

Unlike the Cobb-Douglas function, the translog is a flexible functional form that does not impose any restrictions on substitution possibilities between inputs and outputs. Time and its interaction with inputs and outputs is included to capture, possibly biased, technological progress. The data for inputs and outputs are normalized by their geometric mean allowing us to interpret the parameters associated with first-order terms directly as distance elasticities, evaluated at the geometric mean of the data.

5 Results

The complete set of results is provided in Table A1 in the on-line appendix. Table 2 reports the posterior means, standard deviations and 95% ~~credible~~ confidence intervals of the first-order terms of the distance function and the structural parameters. All of the distance function elasticities are statistically significant, as their respective ~~credible~~ confidence intervals do not contain zero (capital is significant only at the 90% ~~credible~~ confidence interval).

Table 2

Posterior means, standard deviations and 95% ~~credible~~ confidence intervals of the first-order terms and the structural parameters

Variable	**Mean**	**SD**	**95% ~~Credible~~ Confidence Interval**
intercept	-0.46	0.03	[-0.54, -0.42]
log_other	0.12	0.00	[0.12, 0.13]
log_capital	-0.01	0.00	[-0.02, 0.00]
log_labor	-0.05	0.01	[-0.07, -0.04]
log_land	-0.08	0.01	[-0.10, -0.06]
log_materials	-0.11	0.01	[-0.13, -0.10]
log_units	-0.45	0.01	[-0.47, -0.42]
log_feed	-0.18	0.00	[-0.19, -0.17]
trend	-0.02	0.00	[-0.02, -0.02]
σ_v	0.09	0.00	[0.09, 0.09]
σ_ϕ	0.15	0.01	[0.13, 0.16]
σ_ψ	0.38	0.03	[0.32, 0.44]
μ	3.03	0.08	[2.88, 3.18]

The distance elasticity with respect to output reflects a measure of the curvature of the frontier and implies that a 1% increase in output other than milk will lead to a 0.12% increase in the distance function, meaning that farms will move closer to the frontier. The negative distance elasticities with respect to inputs state that increases in inputs push the frontier outwards and farms become less efficient, with livestock units having the highest effect. The scale elasticity is 0.88 and reveals that farms operate under decreasing returns to scale. The German dairy sector experiences technological progress as the frontier moves outwards with time. Finally, the value of μ is 3.03 and suggests that inefficiency persistence, ρ, of German dairy farms is rather high. Moving to the parameters associated with the hidden-state process, Figure 1 presents boxplots[8] of the inefficiency persistence parameter and LRTE.

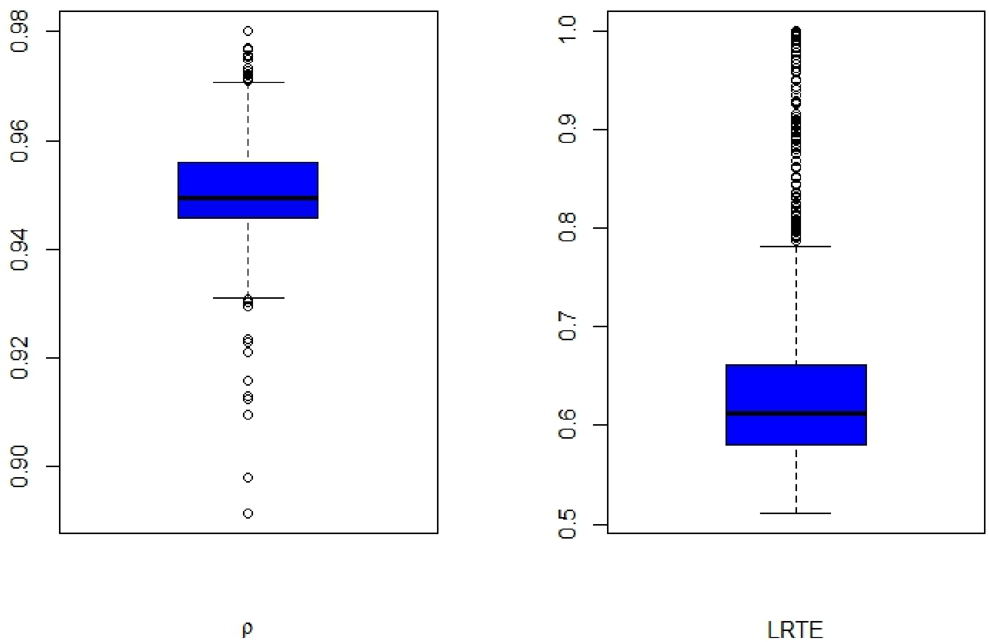

Figure 1. Boxplot of inefficiency persistence parameter $\boldsymbol{\rho}$ and LRTE

The mean value of the inefficiency persistence parameter across farms is 95% while, most farms are concentrated around this mean as can been seen on the left panel of Figure 1. This result is in accordance with the high inefficiency persistence in German dairy farming reported by Emvalomatis et al. (2011). Very few farms exhibit values of inefficiency persistence lower than 90%, while, a few more attain extremely high values of 98%. Hence, despite these small differences, all farms face high adjustment costs that force them to remain inefficient in the fu-

[8] We first calculate the mean of all the draws from the posterior for every farm and then we plot these farm-specific means.

ture. Moreover, given that the s process is stationary, the average value of LRTE is 63%[9] and most of the variation between farms is attributed to their different characteristics (ESUs and subsidies), and, to a lesser extent, to heterogeneity in their inefficiency persistence.

The right panel of Figure 1 shows that most observations are concentrated in the area between the 1^{st} and 3^{rd} quartiles while outliers are found only above the 3rd quartile. The fact that most farms' LRTE is concentrated around 60-80% should not be surprising. Recalling that LRTE reflects the value of efficiency that each farm will attain in the long-run, one should not expect to observe values below 50% since these farms would probably drop out of the market by attaining such a low level of efficiency in the long-run. In contrast, we should expect to find farms to be partly inefficient but in a competitive level such that of 60-80%, while cases of farms' exhibiting a higher level of efficiency in the long-run may occur.

The average LRTE score is somewhat low but this can be explained both by the modelling approach itself and from some facts in German dairy farming. In terms of the modelling approach, the dynamic efficiency model assumes that farms invest in irregular time intervals and they reach the frontier. However, as time progresses, the frontier moves away and farms become less efficient. Technically speaking, in contrast to other efficiency models (i.e. half-normal, exponential) that impose a mode value of 1 for efficiency, in the dynamic efficiency model, efficiency follows a logistic-Normal distribution, and therefore the mode value of efficiency is below unity. When it comes to the German dairy sector, the average LRTE is mainly driven by farms located in southern Germany, where part-time farming is a common phenomenon (Kleinhanß et al., 2010). Indeed, southern farms in Germany comprise 51% of the farms in the sample, and these farms

[9] Note that the expectation of LRTE was defined as $[1 + \exp\{\mathbf{z}_i'\boldsymbol{\delta}/1 - \rho_i\}]^{-1}$.

exhibit the lowest average LRTE score compared to the farms in the remaining regions[10]. Furthermore, the period under consideration is characterized by large milk price changes that may have ~~probably~~ made farmers less efficient as they went out ~~from~~ of their comfort zone and became more prone to committing mistakes. All the ~~aforementioned~~ se reasons may have resulted in the reported low average LRTE score. Similarly, the average value of short-run efficiency across years and farms is 65% meaning that farms can, on average, increase their production by 35%, by still using the same amount of inputs. Besides, the values of short-run efficiency and LRTE are very close to each other meaning that the time-span captured by the data is close to the equilibrium.

Differences in the LRTE of farms can be attributed to farm-specific characteristics. Table A3 in the on-line appendix~~,~~ reports the determinants of transformed technical efficiency s. However, since the main contribution of this paper lies on the explanation of LRTE heterogeneity due to farm-specific characteristics, we derive the marginal effects of the variables in $\mathbf{z}$ on LRTE[11]. These marginal effects were calculated at the mean values of the variables in $\mathbf{z}$ and are presented in Table 3. All marginal effects are statistically significant.

Table 3

Marginal effects of the variables in $\mathbf{z}$ on long-run technical efficiency (LRTE)

Variable	**Mean**	**SD**	**95% ~~Credible~~ Confidence Interval**
ESU	0.01	0.00	[0.01, 0.01]
subsidies	-0.01	0.00	[-0.01, -0.01]

The marginal effect with respect to farm size is positive and implies that an

[10]Table A2 in the Appendix presents the number of farms per region, and the average LRTE for each region in Germany

[11]The derivative of LRTE with respect to the k^{th} explanatory variable in $\mathbf{z}$ is given by: $\frac{\partial LRTE_i}{\partial z_k} = \frac{\left(\frac{z_k}{\rho_i}\right) \times \exp\{\mathbf{z}_i'\boldsymbol{\delta}\}}{(1+\exp\{\mathbf{z}_i'\boldsymbol{\delta}\})^2}$

1 unit (100 ESU) increase in farm size causes a 1% increase in LRTE. This result suggests that larger farms are more likely to attain higher efficiency scores in the long run, possibly because they tend to be more business oriented and make use of more mental labor. Subsidies have a negative marginal effect on LRTE with an 1 unit (100,000€) increase in subsidies leading to a 1% decrease in LRTE. This negative effect can be attributed to the decrease in farmers' motivation to work efficiently when subsidies are seen as an additional source of income. This result is ~~in accordance~~ consistent with the findings of Hadley (2006), Bojnec and Latruffe (2009), Zhu and Oude Lansink (2010), Zhu et al. (2011), Zhu et al. (2012), and Bojnec and Latruffe (2013).

6 Concluding remarks

~~This article~~ We develope~~d~~ a model that accounts for heterogeneity in long-run technical efficiency. A dynamic stochastic frontier model is used, which, as an alternative to the generalized true random effects model, can provide a value ~~of~~ for the long-run efficiency of farms. However, our model recognizes that long-run technical efficiency may be affected by firm-specific characteristics, which is an issue that has been completely ignored in previous studies that have used either the dynamic stochastic frontier or the generalized true random effects model. Furthermore, it also accounts for potential differences in firms' inefficiency persistence using a novel approach that maintains the assumption of positive autocorellation of efficiency under the presence of high adjustment costs. Hence, our modeling approach allows the long-run expected value of technical efficiency to differ among firms based on two components: differences in firm-specific factors and potentially different degrees of inertia of firms in adjusting their quasi-fixed factors under the presence of high adjustment costs. The model is applied to an unbalanced panel dataset of German dairy farms that covers the period from 1999 to 2009 using ~~and~~ a Bayesian estimation approach ~~is proposed~~.

Our results confirm the presence of highly autocorellated inefficiency as the model produces an estimate of average inefficiency persistence of 95%. Governmental regulation and unpredictable changes in economic conditions force farms to remain inefficient and this inefficiency does not disappear as time progresses. Credit access problems or time-consuming learning-by-doing procedures suggest that the convergence towards more efficient use of resources is costly and, therefore, gradual. Heterogeneity in inefficiency persistence is found to be low, suggesting that farmers exhibit a similar degree of sluggish adjustment towards more efficient production plans. High risk-aversion when it comes to the adoption of a new technology in combination with adjustment costs may be responsible for such similarities in inefficiency persistence.

The average value of long-run technical efficiency is 63%, confirming that the presence of high adjustment costs provides farmers with an incentive to remain partly inefficient at a given point in time. Most farms attain long-run efficiency scores of 60-80%, while few of them reach higher efficiency levels in the long-run. The fact that there exist no farms that attain long-run efficiency scores below 60% is anticipated based on the argument that very inefficient farms should not be able to survive in the long-run due to market competition. One should rather expect that most farms would reach a high level of efficiency in the long-run that can allow them to continue operating. Differences in long-run technical efficiency of farms are attributed, to a large extent, to farm-specific factors and, to a lesser extent, to heterogeneity in inefficiency persistence.

European size units are positively related with long-run technical efficiency, suggesting that larger farms, in terms of economic size units, are more efficient in the long-run. This result is justified based on the fact that larger farms are more business/market oriented and more ~~prone~~ likely to the use of ~~mental labor~~ managerial labour that can increase their efficiency. Subsidies are negatively associated with long-run technical efficiency. Several studies have shown that when subsidies are perceived as an additional source of income, they lead to lower motivation of farm operators to improve the efficiency of their farms. This income effect is particularly true for the period under study, since, after the 2003 Common Agricultural Policy (CAP) reform, subsidies were disbursed in the form of decoupled payments which were independent from production quantities.

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On-Line **Appendix**

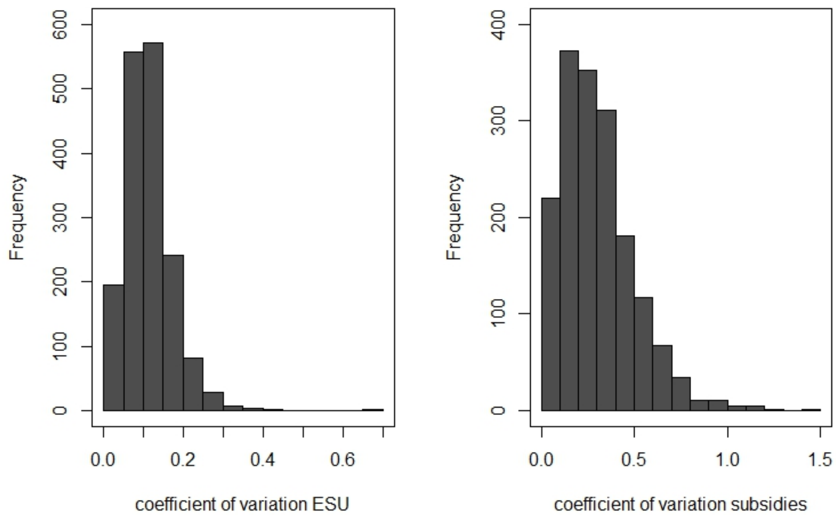

Figure A1. Coefficient of variation for European Size Units and subsidies

Table A1

Estimates of the model's parameters

Variable	Mean	SD	95% Credible Interval
intercept	-0.46	0.03	[-0.54, -0.42]
log_y2	0.12	0.00	[0.12, 0.13]
log_K	-0.01	0.00	[-0.02, 0.00]
log_L	-0.05	0.01	[-0.07, 0.04]
log_A	-0.08	0.01	[-0.10, -0.06]
log_M	-0.11	0.01	[-0.13, -0.10]
log_S	-0.45	0.01	[-0.47, -0.42]
log_F	-0.18	0.00	[-0.19, -0.17]
trend	-0.02	0.00	[-0.02, -0.02]
east	0.03	0.01	[0.00, 0.06]

Variable	Mean	SD	95% Credible Interval
west	-0.04	0.01	[-0.06, -0.01]
north	0.03	0.01	[0.01, 0.05]
log_KK	0.01	0.00	[0.01, 0.01]
log_KL	-0.01	0.01	[-0.03, 0.01]
log_KA	-0.02	0.01	[-0.04, 0.00]
log_KM	0.05	0.01	[0.03, 0.06]
log_KS	-0.03	0.01	[-0.05, -0.01]
log_KF	-0.00	0.00	[-0.01, 0.01]
log_LL	0.02	0.01	[-0.01, 0.04]
log_LA	0.03	0.02	[-0.01, 0.06]
log_LM	0.01	0.02	[-0.03, 0.03]
log_LS	-0.04	0.02	[-0.08, 0.01]
log_LF	0.02	0.01	[0.01, 0.04]
log_AA	0.01	0.01	[-0.02, 0.04]
log_AM	0.03	0.02	[-0.00, 0.07]
log_AS	-0.08	0.03	[-0.13, -0.03]
log_AF	0.03	0.01	[0.01, 0.04]
log_MM	0.00	0.01	[-0.01, 0.02]
log_MS	-0.16	0.02	[-0.20, -0.12]
log_MF	0.03	0.01	[0.02, 0.04]
log_SS	0.12	0.02	[0.08, 0.17]
log_SF	0.03	0.01	[0.01, 0.05]
log_FF	-0.04	0.00	[-0.04, -0.04]
log_y2y2	0.03	0.00	[0.03, 0.03]
trend2	0.00	0.00	[0.00, 0.00]
log_Ky2	-0.00	0.00	[-0.01, 0.00]

Variable	Mean	SD	95% Credible Interval
log_Ly2	-0.01	0.01	[-0.02, 0.00]
log_Ay2	-0.03	0.01	[-0.04, -0.02]
log_My2	0.05	0.01	[0.04, 0.06]
log_Sy2	0.01	0.01	[-0.01, 0.03]
log_Fy2	-0.01	0.00	[-0.01, -0.00]
trend_log_K	0.00	0.00	[-0.00, 0.00]
trend_log_L	-0.01	0.00	[-0.01, -0.00]
trend_log_A	0.00	0.00	[0.00, 0.01]
trend_log_M	0.01	0.00	[0.01, 0.01]
trend_log_S	-0.01	0.00	[-0.01, -0.00]
trend_log_F	0.00	0.00	[0.00, 0.00]
trend_log_y2	0.01	0.00	[0.01, 0.01]
s			
intercept	0.01	0.00	[0.00, 0.02]
ESU	0.04	0.00	[0.03, 0.04]
subsidies	-0.03	0.01	[-0.04, -0.02]
σ_v	0.09	0.00	[0.09, 0.09]
σ_ξ	0.15	0.01	[0.13, 0.16]
σ_ω	0.38	0.03	[0.32, 0.44]
μ	3.03	0.08	[2.88, 3.18]

Table A2

Number of farms and mean long-run technical efficiency (LRTE) for each region in Germany

region	**number of farms**	**mean LRTE**
east	102	0.72
west	294	0.63
north	439	0.68
south	856	0.60

Table A3

Determinants of transformed efficiency s

Variable	**Mean**	**SD**	**95% Credible Interval**
intercept	0.01	0.00	[0.00, 0.02]
ESU	0.04	0.00	[0.03, 0.04]
subsidies	-0.03	0.01	[-0.04, -0.02]